Federated Learning Approach for Passenger–Centric Infotainment Services in Autonomous Cars
Anselme Ndikumana, Choong Seon Hong
Department of Computer Science and Engineering, Kyung Hee University, Rep. of Korea
{anselme, cshong}@khu.ac.kr

Abstract
In the car, the choice of infotainment contents depends on the features of car’s passengers. Therefore, autonomous cars should learn themselves and understand passengers’ features for delivering the appropriate contents to the passengers. However, smart devices such as smartphones have revolutionized the current society. Passengers do not care too much about in–car infotainment; they find more convenient to use their smart devices for infotainment services. Therefore, learning passengers’ features using images captured by autonomous car’s camera will be not enough to provide enhanced infotainment services. Therefore, the autonomous car should use images from its camera and data from the passenger’s devices. However, the passenger’s devices have private data which are sensitive to privacy. Therefore, to address these challenges, we propose a federated learning approach that enables the autonomous car to learn passengers’ features using their devices (without taking their data) while keeping privacy. First, the autonomous car uses Convolutional Neural Network (CNN) to make a global model for predicting passengers’ features. Then, shares the model with the passenger’s devices. Second, any passenger who wants enhanced infotainment services uses the CNN model and its data to improve the model and share only learning parameters with the autonomous car. Finally, the autonomous car does aggregation and averaging of learning parameters for improving the global model. The performance evaluation shows that the proposed federated learning approach can be easily implemented in autonomous cars.

1. Introduction
For an intelligent autonomous car, it needs to have smart sensors and analytics applications that help in collecting and analyzing real–time data related to driving environments inside and outside the car. To achieve this the autonomous car should be equipped with an On–Boarding Unit (OBU) with the Graphics Processing Unit (GPU) for handling computation, storing, and communication [1,2,3]. Moreover, the automobile industry is now focusing on the next generation of autonomous driving, i.e., the self–driving car, where the autonomous car will have fully automation driving in a realistic and real–time environment. Therefore, it was predicted that if everyone in the US uses self–driving cars, there will be 22 extra billions of hours in media consumption time [4].
To entertain passengers, autonomous cars should deliver various infotainment contents using recent technologies such as mixed reality. However, the choice of infotainment contents depends on the features of autonomous cars’ passengers, where passengers with different emotions, gender, location, age, and time choose different entrainment contents [2]. Therefore, to satisfy passengers, autonomous cars should learn and understand their passengers’ features. Furthermore, smart users’ devices such as the smartphones, tablets, and many more have modernized the current society, where people spend more time with their smart devices. However, inside the autonomous cars, passengers do not care too much about in–car infotainment, they prefer to use their smart devices for infotainment services. Therefore, learning passengers’ features using images from the autonomous car’s camera will be not sufficient to provide enhanced and passenger–centric infotainment services. Therefore, autonomous cars should be assisted by the passenger’s devices in learning the passenger’s features and identifying infotainment contents associated with these features.
We consider that the passenger’s devices have private data that are sensitive to privacy. To address the above–highlighted challenges, while keeping the privacy of passengers, we consider federated learning as a suitable approach to use at passengers’ devices because it is a distributed learning approach which is privacy–friendly [5,6]. Therefore, in this paper, we propose a federated learning–based approach that allows the autonomous car to learn passengers’ features using their devices and without taking their data. In our approach, the autonomous car uses CNN to make a global model for predicting passengers’ features. Then, it shares the model with passengers’ devices. Any passenger who wants enhanced infotainment service uses the CNN model and its data to improve the model and share only learning parameters with the autonomous car. In other words, we consider that having enhanced infotainment services as motivation for passengers to participate in federated learning.
Finally, the autonomous car does aggregation and averaging of learning parameters received from the passengers for improving the global model.
This work is an extension of our previous work in [2] and described in Fig. 1, where CNN as a global model is used to predict autonomous car occupants’ features using facial images of passengers captured using the car’s camera. Furthermore, in this work, the global CNN model uses passengers’ devices to predict their features, where each passenger uses the model and shares only learning parameters with the autonomous car.
device to predict its features and for improving the model. Thus, the passenger’s data is sensitive to privacy, there is no need to share the passenger’s data with the autonomous car.

5. After predicting feature using the CNN model and the passenger’s data, each passenger shares learning parameters such as weights with the autonomous car’s OBU.

6. On receiving learning parameters from passengers, the autonomous car’s OBU aggregates the parameters through averaging and updates the CNN model. Then, the autonomous car uses model and facial images from its camera to predict passenger features and identifies the infotainment contents that correspond to passengers’ features.

Figure 1: An illustration of the existing model.

2. Federated Learning Approach for Passenger-centric Infotainment Services

2.1. Global Model: Convolutional Neural Network

For the global model, we propose to use CNN to predict the passengers’ features such as emotion, age, gender, and location using dataset. As described in [2], we consider that the users choose infotainment contents based on these features. We use $k_0$ to denote facial image input at the input layer, while $k_j$ denotes the feature map at layer $j$. In addition to that, we use $y = H(k_j)$ to denote a nonlinear transformation applied to the feature map $k_j$, where $y = H(k_j)$ is mathematically expressed as follows:

$$H(k_j) = f(k_j) + k_j.$$  \hspace{1cm} (1)

We use $F(k_j)$ to define learning function. Therefore, we can express feature map $k_{j+1}$ after convolution layer $j$ as follows:

$$k_{j+1} = \text{ReLU}(\text{conv}(k_j) + k_j).$$  \hspace{1cm} (2)

In (2), we use $\text{conv}(k_j)$ to define the output of the convolution layer $j$, where the output of the convolution layer $j$ is given as input of rectified non-linearity (ReLU) function. The ReLU helps to overcome the problem of vanishing gradient characterized the neural network. The ReLUs is applied to the last layer for predicting class labels (such as emotion, age, gender) of facial images.

2.2. Federated Learning (FL) Approach

We consider the data center to be in the far distance from autonomous cars. Therefore, to reduce communication delay, the autonomous car can download the tested and trained the CNN model from the data center and use it for predicting passengers’ features. The workflow of our federated learning approach is depicted in Fig. 2 and described as follows:

1. In the first step, the autonomous car downloads the CNN model from DC and store it.
2. To have an enhanced infotainment service, each passenger who needs personalized service sends interest to the autonomous car’s OBU.
3. The autonomous car’s OBU replies by sending the CNN model to the passenger.
4. The passenger uses the CNN model, its data, and

Figure 2: Federated learning system for infotainment services. In Fig. 2, the steps from 2 to 5 are performed at each device of the passenger who sends an interest to the autonomous car for personalized infotainment service. In other words, the passenger who does not send interest to the autonomous car, it is not involved in the federated learning approach. Furthermore, to deploy the federated learning approach, we consider that each autonomous car is equipped with charging slots that can be used to charge the devices of passengers. Therefore, there is no energy constraint for running CNN local model on the passenger’s device. In our approach, we $U$ to denote a set of the autonomous car’s passengers and $U_F \subseteq U$ to denote a subset of $U$ for the passengers interested in participating in our federated learning approach. Furthermore, we use $M \in \mathbb{R}^{d_1 \times d_2 \times d_3 \times d_4}$ to denote matrix parameters of our CNN-based federated learning in $5$ dimensions composed of input ($d_1$), width ($d_2$), height ($d_3$), color’s channels ($d_4$), and output ($d_5$).

We use $M_t$ to denote current model parameters at a time $t$, where the autonomous car sends the model and corresponding parameters $M_t$ to passengers. Then, each passenger uses its images as inputs to predict its features and update model independently. We use $M_t^1, ..., M_t^{i_t}$ to denote the current local model of the passengers participating
Join MLP and Federated Learning (CNN-based) [2]. in the federated learning, where the local model updated at each passenger $u \in U_P$ can be written as follows:

$$P_{i}^u = M_{i} - M_{0}$$  (3)

Each passenger $u \in U_P$ shares the model updated parameter matrix $P_{i}^u$ with the autonomous car’s OBU, where the autonomous car performs the aggregation of the received matrix of parameters from passengers. The model parameter aggregation is mathematically expressed as follows:

$$P_{i} = \frac{1}{|U_P|} \sum_{u=1}^{U_P} P_{i}^u.$$  (4)

On the other hand, the global model update in the autonomous car can be mathematically expressed as follows:

$$M_{t+1} = M_{t} + \gamma P_{i}$$  (3)

where $\gamma$ is the learning parameter. Then, after updating the model the autonomous car uses the global model and passengers’ images captured by its camera to learning passengers’ features.

2.3 Join Multi-Layer Perceptron and Federated Learning for Infotainment Services

The objective of predicting the features of the autonomous car’s passengers is to identify the contents that meet these features in order to give passengers the appropriate infotainment contents. Here, we assume the proposed Multi-Layer Perceptron (MLP) in our previous work in [2] is already deployed in an autonomous car. In the MLP output, we have infotainment contents which are appropriate to certain features such as age, gender, and location. Then, the autonomous car joins MLP output and federated learning (CNN based) using k-means and binary classification described in [2,7] to identify the infotainment contents that meet passengers’ features. The whole process is summarized in Fig.3.

3 Performance Evaluation

For the performance evaluation, we test the feasibility of our proposal using Pyssft library, MNIST dataset, and the basic federated learning model described in [8]. In this model, we use 7 workers (here, called passengers), batch size is set to 32, learning rate equals to 0.001, and the number of epochs equals to 5. Our prediction reaches 96% of accuracy. To minimize errors in our prediction, we use cross-entropy function. The simulation results for cross-entropy function minimization is presented in Fig. 4. However, this work is in its early stages of development. As a future direction, we aim to extend it with more details and performance evaluation using the dataset for facial images.

4 Conclusion

In this paper, we presented a federated learning outlook for passenger-centric infotainment services in autonomous cars. In the proposed approach, the autonomous car uses CNN to make a global model for predicting passengers’ features. Then, share the model with the passenger devices. Then, any passenger who wants a personalized service uses the CNN model and its data to improve the model and share learning parameters with the autonomous cars, without sharing data. Finally, the autonomous performs aggregation and use the model to predict passengers’ features and identify infotainment contents that meet predicted features. Our discussion shows that the proposed federated learning approach can be easily implemented in autonomous cars.

5 Acknowledgement

This work was supported by Institute for Information & Communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No.2015–0–00557, Resilient/Fault-Tolerant Autonomic Networking Based on Physicality, Relationship and Service Semantic of IoT Devices). Dr. CS Hong is the corresponding author.

References


Figure 3: Join MLP and Federated Learning (CNN-based) [2]. in the federated learning, where the local model updated at each passenger $u \in U_P$ can be written as follows:

$$P_{i}^u = M_{i} - M_{0}$$  (3)

Each passenger $u \in U_P$ shares the model updated parameter matrix $P_{i}^u$ with the autonomous car’s OBU, where the autonomous car performs the aggregation of the received matrix of parameters from passengers. The model parameter aggregation is mathematically expressed as follows:

$$P_{i} = \frac{1}{|U_P|} \sum_{u=1}^{U_P} P_{i}^u.$$  (4)

On the other hand, the global model update in the autonomous car can be mathematically expressed as follows:

$$M_{t+1} = M_{t} + \gamma P_{i}$$  (3)

where $\gamma$ is the learning parameter. Then, after updating the model the autonomous car uses the global model and passengers’ images captured by its camera to learning passengers’ features.

2.3 Join Multi-Layer Perceptron and Federated Learning for Infotainment Services

The objective of predicting the features of the autonomous car’s passengers is to identify the contents that meet these features in order to give passengers the appropriate infotainment contents. Here, we assume the proposed Multi-Layer Perceptron (MLP) in our previous work in [2] is already deployed in an autonomous car. In the MLP output, we have infotainment contents which are appropriate to certain features such as age, gender, and location. Then, the autonomous car joins MLP output and federated learning (CNN based) using k-means and binary classification described in [2,7] to identify the infotainment contents that meet passengers’ features. The whole process is summarized in Fig.3.

3 Performance Evaluation

For the performance evaluation, we test the feasibility of our proposal using Pyssft library, MNIST dataset, and the basic federated learning model described in [8]. In this model, we use 7 workers (here, called passengers), batch size is set to 32, learning rate equals to 0.001, and the number of epochs equals to 5. Our prediction reaches 96% of accuracy. To minimize errors in our prediction, we use cross-entropy function. The simulation results for cross-entropy function minimization is presented in Fig. 4. However, this work is in its early stages of development. As a future direction, we aim to extend it with more details and performance evaluation using the dataset for facial images.

4 Conclusion

In this paper, we presented a federated learning outlook for passenger-centric infotainment services in autonomous cars. In the proposed approach, the autonomous car uses CNN to make a global model for predicting passengers’ features. Then, share the model with the passenger devices. Then, any passenger who wants a personized service uses the CNN model and its data to improve the model and share learning parameters with the autonomous cars, without sharing data. Finally, the autonomous performs aggregation and use the model to predict passengers’ features and identify infotainment contents that meet predicted features. Our discussion shows that the proposed federated learning approach can be easily implemented in autonomous cars.

5 Acknowledgement

This work was supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No.2015–0–00557, Resilient/Fault-Tolerant Autonomic Networking Based on Physicality, Relationship and Service Semantic of IoT Devices). Dr. CS Hong is the corresponding author.

References


